Comparison of EM + particle filtering and optimization for nonlinear state-space identification

Koen Tiels, Andreas Svensson, Thomas B. Schön

$$x_{t+1} = Ax_t + Bu_t + E\Phi(x_t, u_t) + v_t$$
$$y_t = Cx_t + Du_t + F\Phi(x_t, u_t) + e_t$$

v_t → process noise

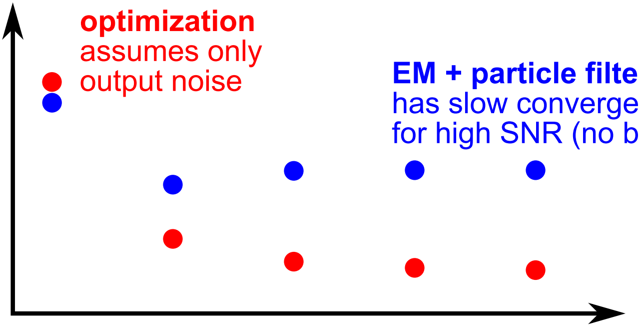
e_t → output noise

$\Phi(x_t, u_t)$ → sine basis functions

parameter estimation → EM + particle filter

parameter estimation → optimization

EM + particle filter ↕ optimization: comparison



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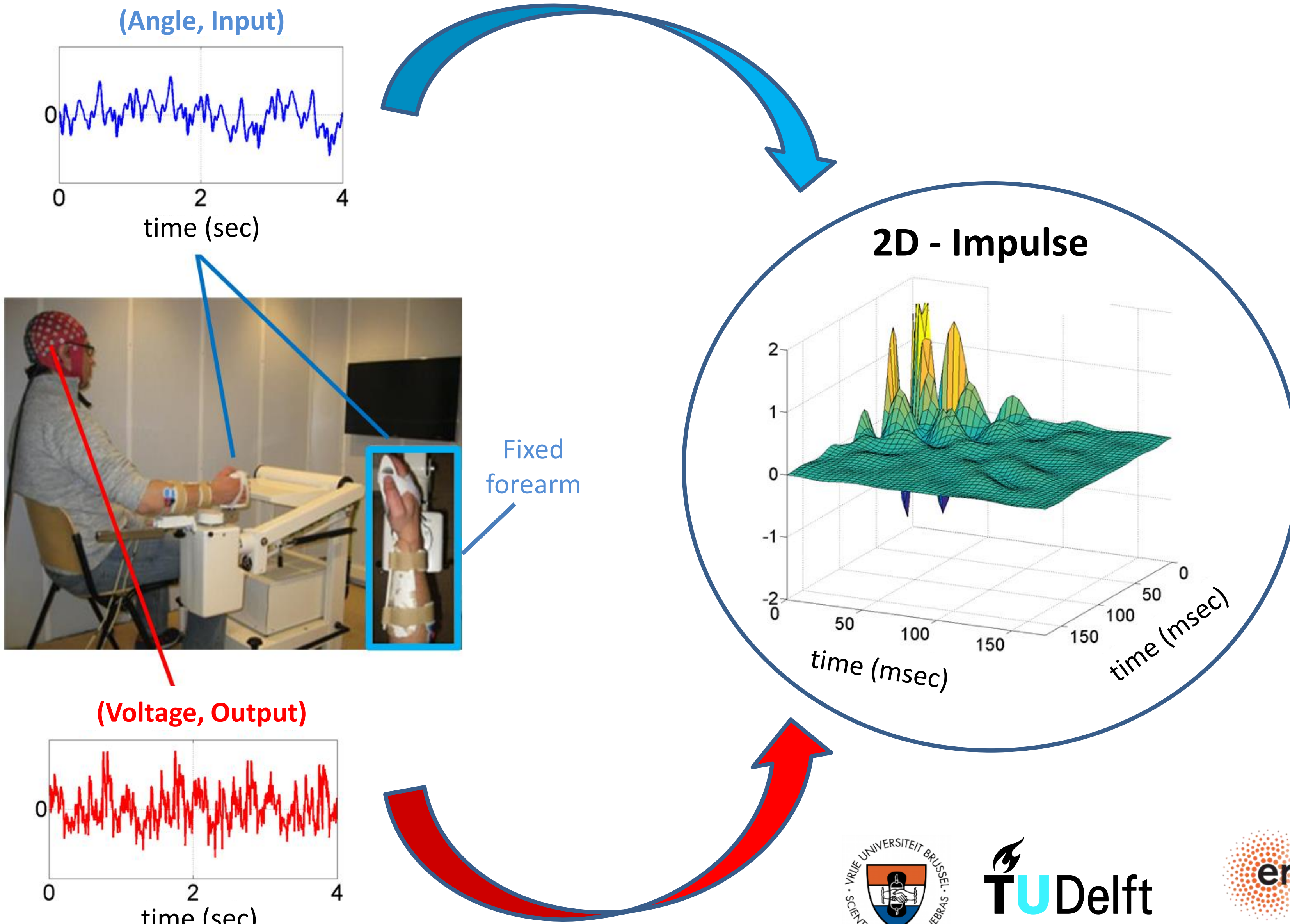
Volterra series model of the brain response to imposed wrist motion

Georgios Birpoutsoukis, Martijn P. Vlaar, John Lataire, Maarten Schoukens, Alfred C. Schouten, Johan Schoukens, and Frans C.T. van der Helm



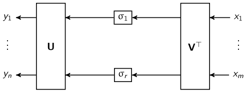
Non-linear singular value decomposition

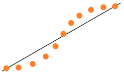
Mariya Ishteva and Philippe Dreesen

data

$$\mathbf{y} = \mathbf{A}\mathbf{x} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\top\mathbf{x}$$

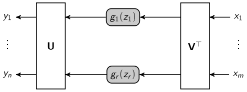
- low-rank representation
- singular value decomposition
- extract linear relations

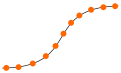




$$\mathbf{y} = \mathbf{f}(\mathbf{x}) = \mathbf{U}\mathbf{g}(\mathbf{V}^\top\mathbf{x})$$

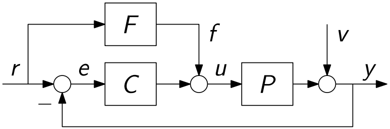
- decoupled nonlinear function
- nonlinear SVD
- extract nonlinear relations





Identification of Inverse Models for Feedforward Control

Non-Causal Basis Functions & Optimal IV Approach



Perfect tracking (e small) achieved if $F = P^{-1}$

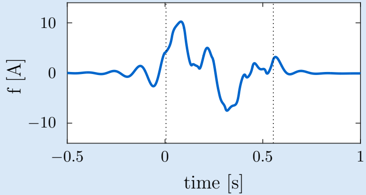
$\Rightarrow$ Aim: identification of P^{-1} for feedforward

Non-Causal Basis Functions

Typical ID: focus on stable systems P

However: no guarantee P^{-1} stable (NMP zeros)

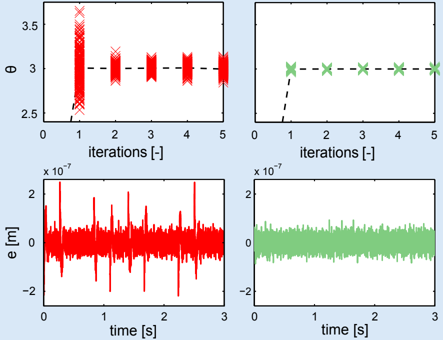
$\Rightarrow$ rational basis functions in $\mathcal{L}_2$: $f \in \ell_2(-\infty, \infty)$



Closed-loop ID setting with extremely low SNR

$\Rightarrow$ IV approach (left), still poor results due to SNR

$\Rightarrow$ optimal IVs (right) for minimized e



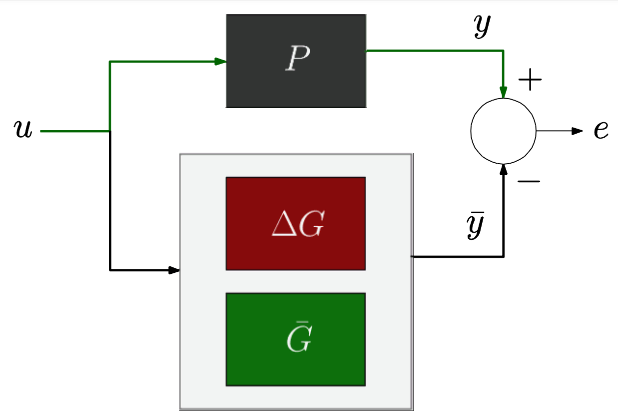
Lennart Blanken & Tom Oomen. Poster session C, P4

Data-driven Model Completion Using Symbolic Regression

D. Khandelwal, P.A. Raijmakers, R. Tóth, S. Weiland

ERNSI Meeting, 2017

Problem Statement



$F(\Delta G)$

Given:

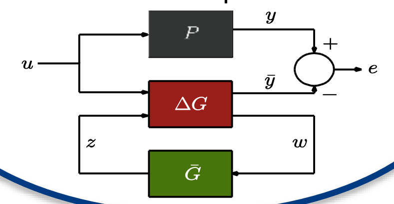
- Model $\bar{G}$
- Data $D_N = \{u(1), y(1), \ldots, u(N), y(N)\}$

Model Completion Problem

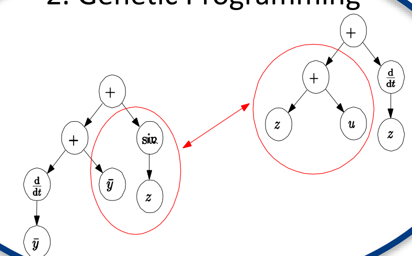
$$\underset{F(\Delta G)}{\text{minimize}}\ e^\top e$$

Solution Strategy

1. Fractional Representation



2. Genetic Programming



3. Least Squares Support Vector Machine (LS-SVM)

$$\hat{y}(t) = w^\top \varphi(t) + b$$

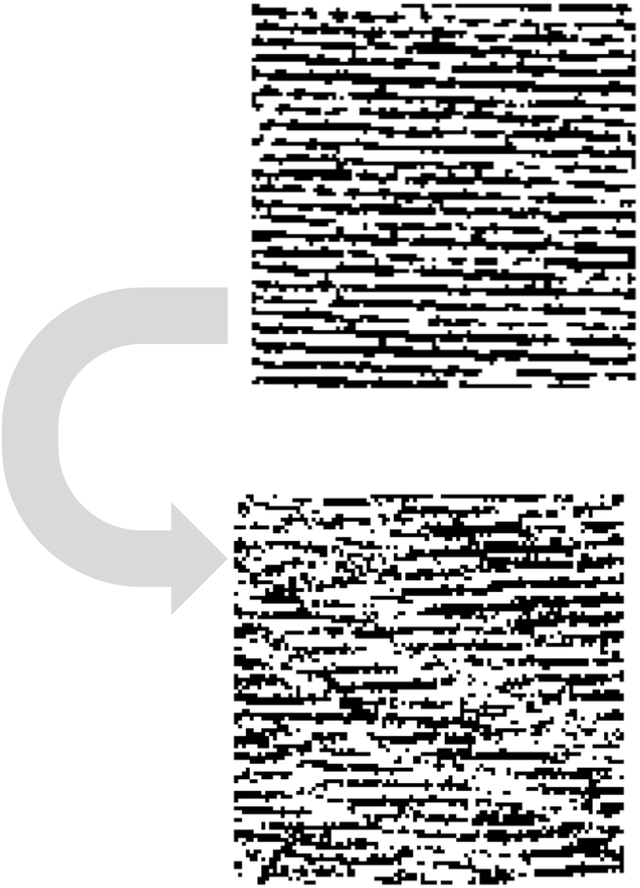
$$K(t_i, t_j) = \varphi(t_i)^\top \varphi(t_j)$$

Texture generation and Wiener system identification by multidimensional rational covariance extension

Axel Ringh, Johan Karlsson, and Anders Lindquist

- Identification of 2D Wiener system with thresholding as nonlinearity
  - Identify threshold parameter
  - Use covariances to identify linear system

- Application to texture generation



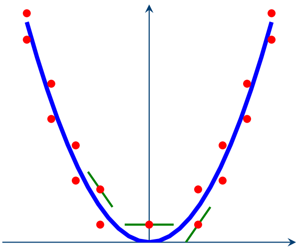
Probabilistic line searches using quintic spline models

Manon Kok and Carl Edward Rasmussen
Department of Engineering, University of Cambridge, UK

Motivation:

We are interested in optimising a function but we only have access to noisy evaluations of the function values.

- The *search direction* is accurate.
- We focus on determining the *step length* along this search direction.



Approach:

- We build a fully probabilistic model using all available information and sensible prior assumptions modelling the function as
  - a quadratic
  - a deviation from the quadratic.

Krylov methods for low-rank commuting generalized Sylvester equations

Emil Ringh

Dept. Math.

Joint work with: E. Jarlebring (KTH), G. Mele (KTH), D. Palitta (Bologna)

Problem: Generalized Sylvester equation

$$AX + XB^T + \sum_{i=1}^{m} N_i X M_i^T = C_1 C_2^T$$

Application: Bilinear control systems

$$\begin{aligned} \dot{x}(t) &= Ax(t) + \sum_{i=1}^{m} N_i x(t) u_i(t) + Cu(t), \\ y(t) &= Dx(t) \end{aligned}$$

Recursive Identification with Weighted Null-Space Fitting

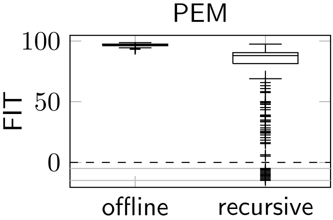
Recursive identification: update model parameters as data are collected

Recursive PEM:

approximations

$\Downarrow$

convergence problems



Idea: use weighted null-space fitting (WNSF)

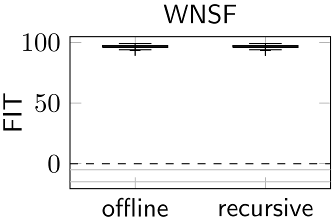
weighted least-squares method with intermediate non-parametric ARX model

Recursive WNSF:

no approximations

$\Downarrow$

same performance as offline



Inverse filtering for hidden Markov models

Robert Mattila, Cristian Rojas, Vikram Krishnamurthy (Cornell Tech) and Bo Wahlberg

- **Optimal filter:**
  Given y_k, provide posterior π_k over the state x_k
- **Inverse problem:**
  Given posteriors π_k, is it possible to recover
  - the observations y_k?
  - the parameters of the sensor?
  - both?
- **Answer:** Yes, yes, yes!
  - *Naive solution*: Expensive mixed-integer linear program
  - *Analytic solution*: Exploit structure of HMM filter
- **Applications:** fault detection, sensor diagnostics, finance (inverse portfolio optimization), electronic warfare, ...

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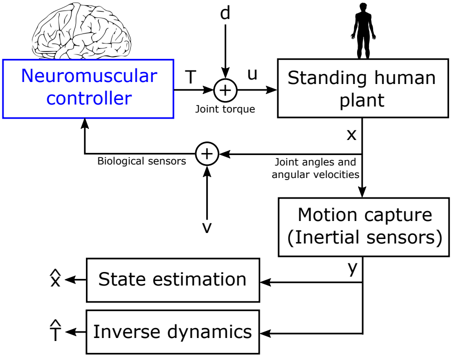
Quantifying human balance control using Gaussian process regression and inertial sensors

Fredrik Olsson and Kjartan Halvorsen

- **The problem:** To identify the **neuromuscular controller** in standing human balance.
- **The method:** We investigate how Gaussian process regression may be used to solve this.
- **Initial results:** Results from simulations of a simple dynamic model of standing human balance is presented and will be discussed.



Linearly constrained Gaussian processes

Problem: How do we encode linear constraints in the covariance function of a multi-output Gaussian process?

$$\mathbf{f}(\mathbf{x}) \sim \mathcal{GP}\left(\boldsymbol{\mu}(\mathbf{x}),\ K(\mathbf{x}, \mathbf{x}')\right), \quad \mathscr{F}_{\mathbf{x}}\mathbf{f} = \mathbf{0}$$

Solution: Model the target function as a linear transformation of an underlying function, and find the required transformation.

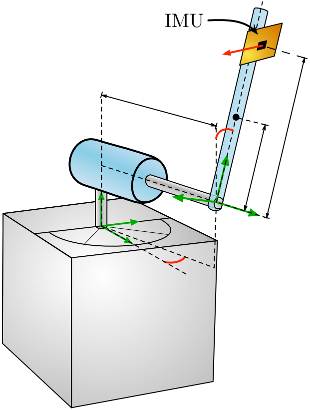
$$\mathbf{f}(\mathbf{x}) = \mathscr{G}_{\mathbf{x}}\mathbf{g} \sim \mathcal{GP}\left(\mathscr{G}_{\mathbf{x}}\,\boldsymbol{\mu}_{\mathbf{g}},\ \mathscr{G}_{\mathbf{x}} K_{\mathbf{g}} \mathscr{G}_{\mathbf{x}'}^{\mathsf{T}}\right), \quad \mathscr{F}_{\mathbf{x}}\mathscr{G}_{\mathbf{x}}\mathbf{g} = \mathbf{0}$$

Example: Reconstructing strain fields from neutron Bragg-edge measurements

Carl Jidling, Niklas Wahlström, Adrian Wills and Thomas B. Schön. **Linearly constrained Gaussian processes.** *Advances in Neural Information Processing Systems (NIPS)*, Long Beach, CA, USA, December, 2017.

Cancellation of Nonlinearities Using Indirect Input Measurements

Jonas Linder and Martin Enqvist



Complex nonlinear mechanical system

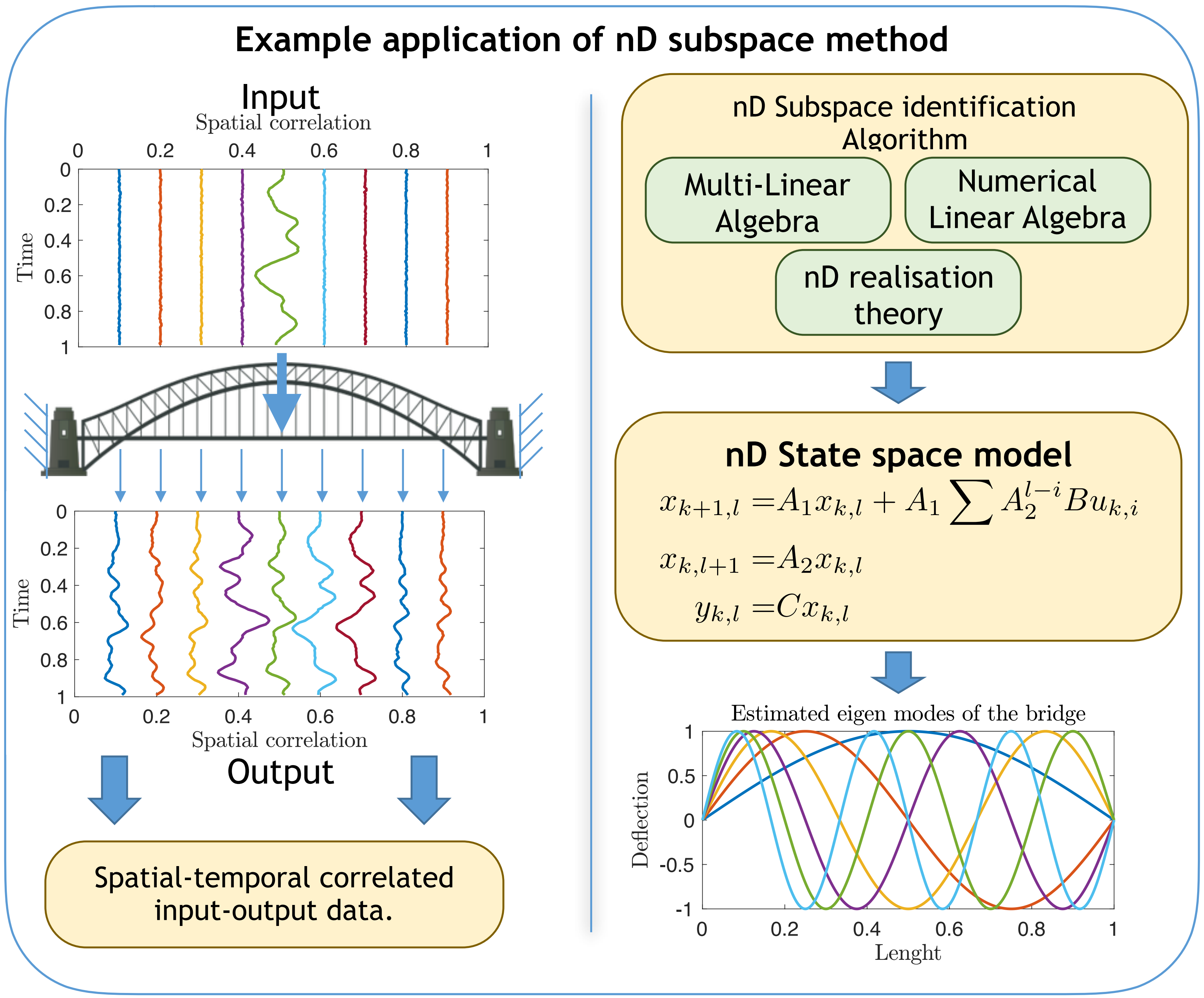
$$\begin{bmatrix} I_0 + I_2\sin^2(\theta_2) & m_2 l_2 L_1\cos(\theta_2) \\ m_2 l_2 L_1 \cos(\theta_2) & I_2\end{bmatrix}\begin{bmatrix}\ddot\theta_1\\ \ddot\theta_2\end{bmatrix} = \begin{bmatrix} -b_1\dot\theta_1 + m_2 l_2 L_1 \sin(\theta_2)\dot\theta_2^2 - I_2\sin(2\theta_2)\dot\theta_1\dot\theta_2 + \tau_1 + \delta_1 \\ -b_2\dot\theta_2 - m_2 l_2 g\sin(\theta_2) + \frac{I_2}{2}\sin(2\theta_2)\dot\theta_1^2 + \tau_2\end{bmatrix}$$

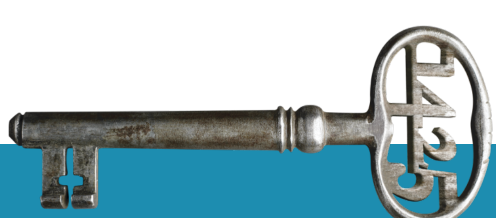
Dynamic Network Concepts

Linear model that correctly describes subsystem

$$(I_2 - m_2 l_2 l_s)\ddot\theta_2 = -b_2\dot\theta_2 - m_2 l_2 a_s - (I_2 - m_2 l_2 l_s)\omega_1\omega_2 + \tau_2$$

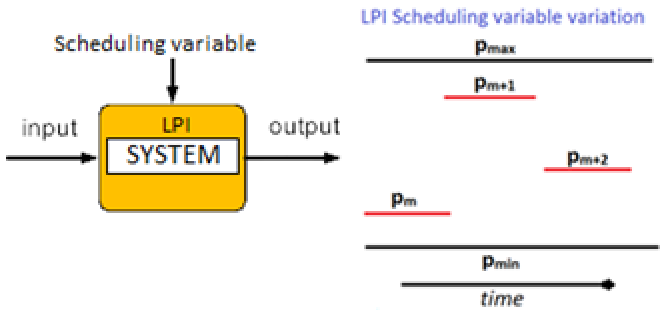
Modeling partial differential equations with state space models.

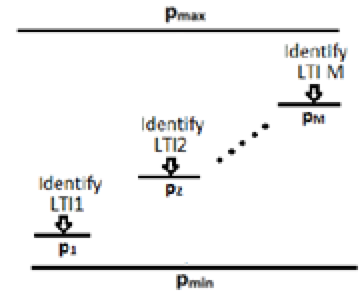




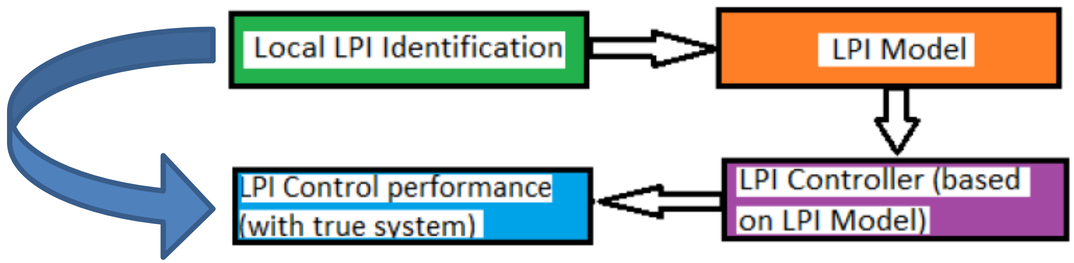
KU LEUVEN

Optimal experiment design for control of LPI systems





Guarantee control performance via optimal design of the identification experiment



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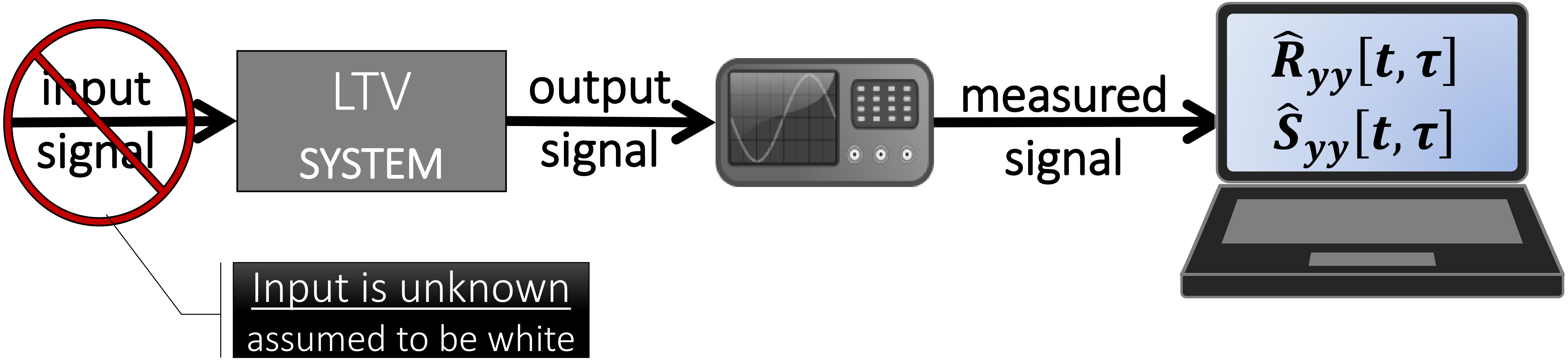
Péter Zoltán Csurcsia

Johan Schoukens and Bart Peeters

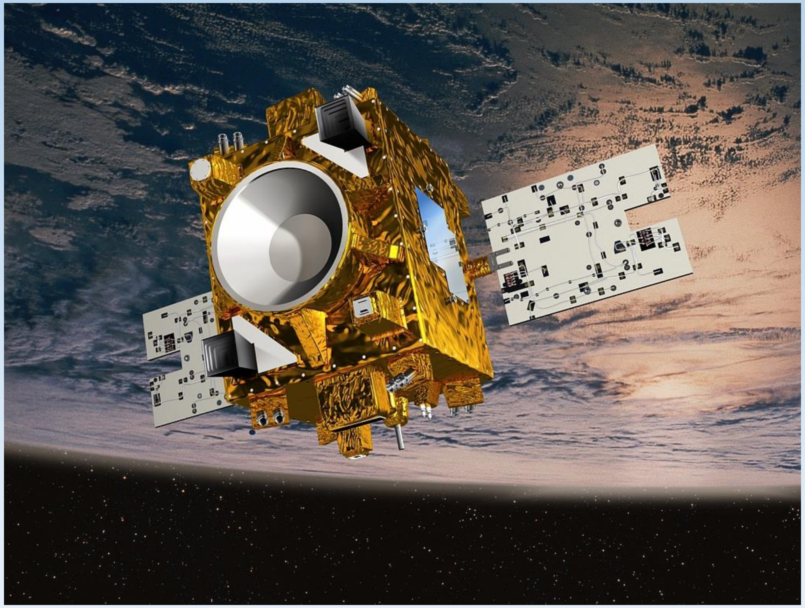
SIEMENS Ingenuity for life

Nonparametric Time-varying Operational Modal Analysis



System identification for attitude control of satellites

C. Nainer, M. Gilson, H. Garnier, C. Pittet



Validation of attitude control algorithms require very accurate satellite models

Some satellite parameters cannot be accurately identified on ground

Parameters identification must be performed during satellite operation

Preliminary results on inertia matrix estimation will be presented

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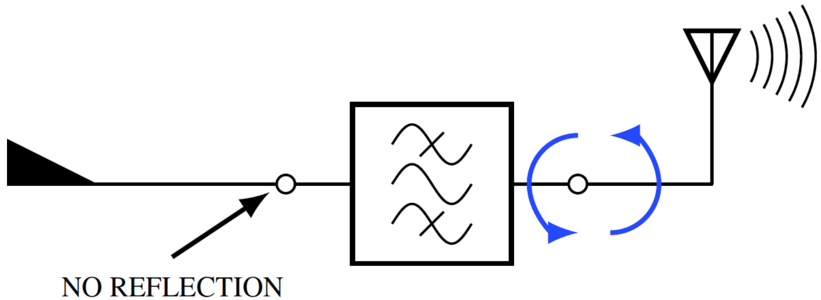
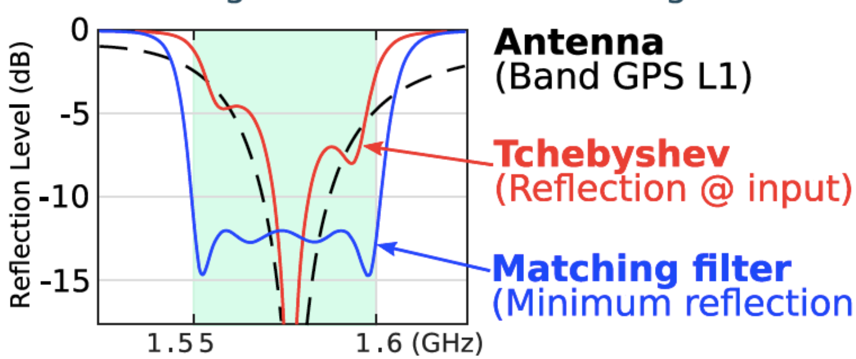
Synthesis methods for matching filters

D. Martinez Martinez, G. Bose, F. Seyfert, M. Olivi, S. Bila, F. Torres, J. Sence



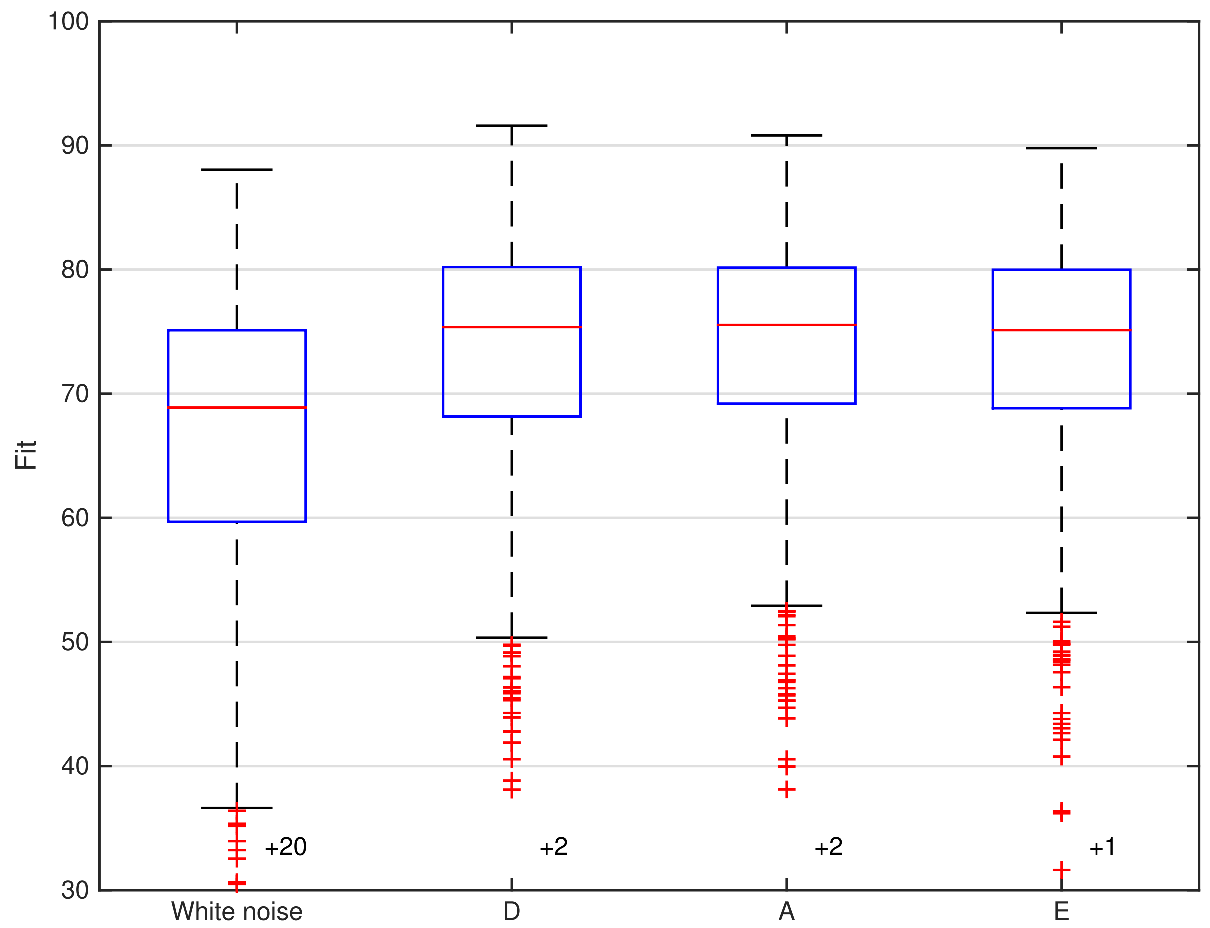
Goal: build a filter that minimizes the reflected power in a passband

Filter of degree 3 for antenna of degree 1



Recent progress on kernel-based regularization methods: Input design

Using the estimated kernel to design the input for a new experiment, the fit of an FIR model can be considerably improved



Biqiang Mu, Tianshi Chen, and Lennart Ljung

LINKÖPING UNIVERSITY
Division of Automatic Control